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Abstract

When examining whether TV advertising has a short-term effect on sales, we have to be careful about the manner in which we deal with the biases caused by confounded covariates on ad exposures and purchases. Otherwise, we may be misled to a spurious correlation of ad exposures and purchases. The recent development of the propensity score method allows us to conduct a rigorous statistical testing on the causal effect of ad exposure on purchase behavior by avoiding these biases. An empirical study suggests that this approach could drastically change the results of simple statistical testing of advertising effects.

Keywords: advertising effectiveness, single-source data, causal effect, confounded covariates, propensity score

Since Jones (1995) questioned whether TV advertising has a short-time effect on sales, this issue has attracted a great deal of attention from marketers, because if such an effect exists, the focus of advertising strategies should shift from the long-term (e.g., brand building) to the short-term or to the “recency” effect (e.g., stimulating purchases immediately). By measuring both TV ad exposures and purchases using single-source data from the same individual households, Jones (1995) proposed computing the ratio of the purchase frequency of households exposed to a TV ad over the purchase frequency of households never exposed to that ad within a week before each purchase. This is termed as Short-Term Advertising Strength (STAS). If this ratio exceeds one, it can be proved that there is a short-term effect of advertising on sales.

Despite its simplicity, which has been maintained to enable practitioners to understand it intuitively, the STAS approach has been criticized by academic researchers (e.g., Lodish 1997) because it lacks not only a statistical testing procedure on difference but also a consideration about the confounding effects of covariates affecting ad exposures and purchases of consumers. Although no agreement has been reached with respect to this controversy (Jones 1998, Lodish 1998), recent textbooks on advertising effectiveness address the impacts and drawbacks of the STAS approach (East 2003, Tellis 2004). East and Tellis both point out that the media plan of an

advertiser who effectively targets the consumers who make heavy purchases would generate a positive association between ad exposures and purchases without there being any causal relationship between them. In such cases, the STAS would reflect a spurious correlation between ad exposures and purchases.

In order to validate the STAS approach by avoiding the biases caused by covariates, Schroeder, Richardson, and Sankaralingam (1997) applied it to the data obtained via a split-cable system through which different TV ads can be conveyed to each household within the area covered by a cable TV service. Since it allows a random assignment of ad exposures to panel households, the effects of the covariates can be cancelled out. The split-cable system has indeed contributed to the accumulation of empirical findings regarding TV advertising effectiveness on sales (e.g., Lodish et al. 1995). However, it has a drawback as well—its limited availability in terms of both region and product category. Therefore, most recent researches on advertising effectiveness have applied choice modeling to single-source data collected in a natural setting (e.g., Tellis 1988, Pedrick and Zufryden 1991, Deighton, Henderson, and Neslin 1994). Although these researches consider the covariates affecting purchases, such as the elements of utility, they rarely consider the covariates affecting ad exposures. Furthermore, the introduction of a selection of covariates into the utility function is often problematic since their

mutual dependence can lead the estimated parameters to have unexpected signs. Moreover, the regression function of purchases on covariates may be a nonlinear function, but the researchers assume linearity; this usually leads to severe biases of estimates. Such difficulties in correct model specification become graver as the number of covariates increases.

Generally, all existing approaches assessing advertising effectiveness have their own limitations and drawbacks. Another approach used, particularly in case wherein the split-cable system is unavailable, is the propensity score method. This method is a powerful solution to avoid biases caused by covariates and applied widely from medical researches to social sciences (e.g., Bingenheimer, Brennan, and Earls 2005). In a marketing-related field, Boehm (2005) and Yanovitzky, Zanutto, and Hornik (2005) applied this method for customer relationship management (CRM) and public health education campaigns, respectively. This method enables the examination of the causality by using naturally observed data as if they were well-controlled experimental data where the assignment of treatment is randomized. However, the results of these previous studies may be less convincing since the conventional propensity score methods adopted by them lack a rigorous procedure for statistical testing. In order to overcome this limitation, Hoshino, Kurata, and Shigemasu (in press) proposed the

Propensity Score Weighted Maximum Likelihood Estimator (PSWME). In this study, we adopt this novel method to obtain a more accurate answer to whether the short-term effect of advertising exists.

The remainder of this paper is organized as follows. In the subsequent section, we describe the fundamental idea of a propensity score and the PSWME approach as its extension. In section 2, we explain the data used. In section 3, we discuss the accuracy of the propensity score estimated and compare the results obtained by the conventional approach and the PSWME approach for the causal effect of short-term ad exposure on purchases. Finally, in section 4, we summarize this paper and discuss its managerial implications as well as its limitations and the directions for future research.

1. METHOD

1.1 The Basic Concept of the Propensity Score

The propensity score method was invented by Rosenbaum and Rubin (1983) to assess the causality of medical treatment when a random assignment of treatments to patients is not permitted due to practical or ethical reasons. This method has been applied in a variety of fields, including marketing-related fields, as discussed in the previous section. In all these applications, the effects of treatments or interventions were assessed using naturally observed data, where the assignment of the treatment could be associated,

more or less, with some covariates.

There is no guarantee that the panel households in the single-source data collected in a natural setting are exposed to advertising purely at random. Hence, a simple comparison such as the STAS that compares advertising effects (e.g., purchase) between the households exposed to ad (ad-exposed) and those not exposed to it (non-ad-exposed) would suffer if ad exposure is dependent on covariates that affect purchases. In order to avoid these biases, the ideal but infeasible way would be to assign a household simultaneously to both complementary conditions of ad-exposed and non-ad-exposed. How can we determine the manner in which non-ad-exposed households will behave when exposed to the ad? This “counterfactual” situation can be inferred by using the propensity score method. In this study, the propensity score refers to the probability that an individual household would be exposed to an ad under a certain circumstance expressed by a set of covariates. Hence, provided the propensity scores are correctly estimated in order to identify whether a household is ad-exposed or not, we can efficiently control for the effects of the covariates by comparing the responses of the ad-exposed and non-ad-exposed groups of households with almost the same propensity score level to the ad.

The underlying concept is illustrated in Table 1; the columns list households by

whether they are actually exposed to a brand's ad ($z = 1$) or not ($z = 0$), and the rows list households by whether they purchase the brand after being exposed to the ad (y_1) or without being exposed to it (y_2). We observe combinations of $\{z = 1, y_1\}$ and $\{z = 0, y_2\}$, while we do not observe combinations of $\{z = 0, y_1\}$ and $\{z = 1, y_2\}$ and therefore, the latter combinations are missing (see also Table 1). The propensity score method can be used to infer what would occur in these missing situations: would a household with a high likelihood of being exposed to the ad buy the product even if it were not exposed to the ad or would a household with a low likelihood of being exposed to the ad buy the product even if it were exposed to the ad. The causal effect (Rubin 1978, Rosenbaum and Rubin 1983) of the ad on purchase is defined here as $E(y_1) - E(y_2)$, where $E(y_1)$ is the average household purchase when the household is exposed to the ad and $E(y_2)$ is the average household purchase when the household is not exposed to the ad. Note that the sample average of y_1 is a good estimate of the average household purchase for the households exposed to the ad, $E(y_1|z = 1)$; this is different from $E(y_1)$.

===== Insert Table 1 here =====

1.2 Conventional Methodology of the Propensity Score

Given covariates, the propensity scores are estimated via binomial response models, such as logistic regression, predicting the probabilities of the occurrence of treatment

(advertising exposure in this study). Matching and stratification are the conventional approaches used to test the causal effect of treatment using the propensity scores (Rosenbaum and Rubin 1983). Matching is a process in which a purchase incidence is selected from the treated and untreated groups, respectively, such that the propensity scores for the members of this pair are as close as possible, and compares the effects observed for the members. Although this method is intuitively understandable, the results could differ with repeated calculations since (1) the pairs are stochastically selected from the two groups and the selection varies within a finite number of steps and (2) the sizes of the two groups are usually imbalanced with some unmatched members left over in the larger group.

On the other hand, stratification appears easier to implement. The members of the two groups are assigned one of several strata based on their propensity scores and a comparison is drawn by strata. Unlike matching, stratification is not stochastic and can utilize all data for analyses. However, the number of tiers into which the propensity scores are to be divided is arbitrary.

Another problem of a conventional propensity score method such as matching or stratification is the lack of a statistically valid procedure for hypothesis testing on the difference in the effect between two groups. All the abovementioned problems can be

overcome by the PSWME method proposed by Hoshino, Kurata, and Shigemasu (in press). They derived an asymptotic distribution of the weighted estimator of an effect using (the estimated) the propensity scores in order to conduct statistical testing of the causality of treatment by minimizing arbitrary operations adopted in matching or stratification.

1.3 The PSWME Approach

The PSWME approach is applied to a statistical test on the difference between ad-exposed and non-ad-exposed groups in the purchase rates of a certain brand. The PSWME of these purchase rates can be expressed as follows:

$$\begin{aligned}\hat{E}(y_1) &= \hat{p}_1^W = \sum_{i=1}^N \frac{z_i}{w_i} y_{1i} \bigg/ \sum_{i=1}^N \frac{z_i}{w_i}, \\ \hat{E}(y_2) &= \hat{p}_2^W = \sum_{i=1}^N \frac{1-z_i}{1-w_i} y_{2i} \bigg/ \sum_{i=1}^N \frac{1-z_i}{1-w_i}.\end{aligned}\tag{1}$$

Here, z_i is a dummy variable of actual ad exposure, taking the value 1 if the household is exposed to the ad at purchase incidence i , and 0 otherwise; y_{1i} is a dummy variable of brand purchase in an ad-exposed incidence i , taking the value 1 if the household purchases a specific brand when the ad is exposed at incidence i , and 0 otherwise; y_{2i} is a dummy variable of brand purchase in an non-ad-exposed incidence, taking the value 1 if the household purchases the product when the ad is not exposed at incidence i , and 0 otherwise; and w_i is a propensity score for incidence i .

On the other hand, if we overlook the propensity scores, the observed purchase rates for the ad-exposed and the non-ad-exposed groups are calculated as follows:

$$\begin{aligned}\hat{E}(y_1 | z = 1) &= \hat{p}_1 = \sum_{i=1}^N z_i y_{1i} / \sum_{i=1}^N z_i, \\ \hat{E}(y_2 | z = 0) &= \hat{p}_2 = \sum_{i=1}^N (1 - z_i) y_{2i} / \sum_{i=1}^N (1 - z_i).\end{aligned}\tag{2}$$

These purchase rates are used in the ordinary statistical test on difference between two groups, which is discussed in any textbook on statistics.

The PSWME of purchase rates can be statistically tested based on an application of Hoshino, Kurata, and Shigemasu (in press). On the basis of the derived asymptotic joint distribution of \hat{p}_1^W and \hat{p}_2^W , given the null hypothesis that there is no difference in these rates between the two groups in the population, it is proved that the difference

$\hat{p}_1^W - \hat{p}_2^W$ has an asymptotically normal distribution with mean 0 and variance

$$\sigma_d^2 = \frac{1}{N} \cdot (1 \quad -1) A^{-1} B A^{-1} \begin{pmatrix} 1 \\ -1 \end{pmatrix},\tag{3}$$

where

$$\begin{aligned}A &= \begin{pmatrix} \frac{1}{p_1} + \frac{1}{1-p_1} & 0 \\ 0 & \frac{1}{p_2} + \frac{1}{1-p_2} \end{pmatrix}, \\ B &= \frac{1}{N} \sum_{i=1}^N \beta_i \beta_i^t, \\ \beta_i &= \left(\frac{z_i}{w_i} \left(\frac{y_{1i}}{p_1} - \frac{1-y_{1i}}{1-p_1} \right), \frac{1-z_i}{1-w_i} \left(\frac{y_{2i}}{p_2} - \frac{1-y_{2i}}{1-p_2} \right) \right)^t.\end{aligned}$$

By using the well-known procedure of z test, we can test whether the purchase rate in

the ad-exposed group differs significantly from the one in the non-ad-exposed group. It should be noted that the PSWME method can be applied to more general parametric models, such as logit/probit choice modeling, structural equation modeling, or latent class analysis, which are popular in marketing research.

2. DATA

We used single-source data provided by Video Research Ltd., a marketing research company in Japan. This data involves approximately 1,000 households living in a relatively narrow urban area, records of the purchase histories of brands, the brand's TV ad exposure on each household's TV set, and the covariates describing each household's demographics, and consumption/TV viewing behaviors. From this dataset, we selected 421 households that had purchased instant coffee at least once in 3 years.

The data was aligned with an individual household's purchase incidence of the product category (instant coffee). The effect of our interest is whether a brand of our interest or another brand is purchased, and the treatment is whether the ad for that brand is viewed by the household at least once within a week before the date of the purchase (Figure 1). The assumption that the short-term effect of TV advertising can last for a week is based on Jones (1995).

===== Insert Figure 1 here =====

The strength of advertising effectiveness might vary in terms of time due to the changes in the strategies of the advertisers and the conditions of the audience. Therefore, we split the 3-year data into 12 quarters and gradually moved the “window” (the time horizon for an analysis) of a year from the second quarter to the last quarter. The reason we skip the first quarter is that covariates used for estimating propensity scores in a certain quarter must involve the variables observed in the previous quarter. Thus, we have 8 windows for a brand (a total of 24 cases). This procedure is illustrated in Figure 2.

===== Insert Figure 2 here =====

3. RESULTS

3.1 Ordinary Statistical Test

As a benchmark, we first conducted the ordinary z test on the difference between ad-exposed and non-ad-exposed groups in terms of purchase rates defined in equation (2). As shown in columns 4 to 8 in Table 2, significant differences were observed in 6 of 24 cases. This implies that the short-term effect of advertising as explained by Jones may be statistically supported in one-third of the cases investigated in this study. Particularly for brand 2, the short-term effect is observed in more than half of the cases. These findings could encourage the manager of this brand to consider advertising as an

instrument that stimulates sales instantaneously rather than one that builds up the brand equity from a long-term viewpoint.

===== Insert Table 2 here =====

3.2 Estimation of the Propensity Score

The propensity scores were estimated via binomial logit analysis discriminating the occurrence of ad exposures with covariates separately in each of the 24 cases. From the single-source data, approximately 30 covariates were collected (Table 3). Some covariates described each household's dynamic behavior with respect to TV viewing or purchasing, while others described their static profiles such as demographics. We should note that dealing with so many covariates renders normal choice modeling more difficult in the specification.

===== Insert Table 3 here =====

Here, it is interesting to note the discriminatory performance of each logistic regression rather than the estimated parameters. Table 4 lists several measures in this regard. Accuracy—the proportion of correct predictions for all incidences used for estimation—appears modestly good, ranging from 0.6 to 0.8 for all brands, while Recall—the proportion of correct predictions within the ad-exposed group—appears to be relatively poor for brand 3; this suggests the relative difficulty of discriminating ad

exposures for a rarely advertised brand. More flexible measures are proposed based on rank correlations in the estimated probability of ad exposures (propensity scores) between ad-exposed and non-ad-exposed groups. The most frequently used measure—c statistics—is mainly distributed between 0.7 and 0.8, implying that these discriminations are sufficiently satisfactory.

===== Insert Table 4 here =====

3.3 Hypothesis Testing Using the PSWME

With these estimated propensity scores, we performed the statistical test based on the PSWME, following the procedure described in 1.3. As shown in columns 9 to 12 in Table 2, the results are striking. In all cases, even in those in which the effects are assessed as being highly significant via the ordinary statistical test, there is no significant short-term effect of advertising.

By controlling for the effects of covariates rigorously, the short-term effect of TV advertising on purchase disappeared. This suggests the existence of factors affecting both ad exposures and purchases, which may yield a spurious association between ad exposures and purchases. As many researchers have warned (Lodish 1997, 1998, East 2003, Tellis 2004), if marketers ignore the effects of covariates, they may be misled in their advertising decision-making process.

It should be noted that these results are limited for a certain product class and a certain period; moreover, these results reveal nothing about the effects on purchases other than the short-term effect discussed by Jones (1995) and others. With regard to the data used, it might be possible to detect the mid- or long-term effect of advertising; however, this is beyond the scope of this paper.

4. DISCUSSION

A controversy on the short-term effect of advertising on sales suggested how difficult it is to balance both practical simplicity and statistical appropriateness (e.g., Jones 1995, 1998, Lodish 1997, 1998). If the emphasis is on practical simplicity, the STAS-like measures proposed by Jones (1995) would be favorable. On the other hand, if the emphasis is on statistical appropriateness, criticism against the STAS shows that careful consideration of covariates is necessary. A random-assignment experiment via the split-cable system is ideal in these two respects but is often limited in its availability in terms of region or product category. Choice modeling that is often adopted in marketing science can efficiently control for covariates only when a few critical covariates are identified; its misspecification would yield serious biases in estimated parameters. In addition, it might appear too sophisticated for managers to understand the results without a familiarity with such advanced methods. In contrast to these existing

approaches, the propensity score method has the following advantages: (1) it can be efficiently applied to naturally observed data where ad exposures are not randomly assigned to households; (2) it does not require prior knowledge about structural causality between covariates and outcome/dependent variables; and (3) it provides a simple criterion, such as the STAS, whereby managers can intuitively and easily understand advertising effectiveness. Moreover, the extension using the PSWME enables rigorous statistical testing of the effect.

Application of this method for instant coffee brands reveals striking results—the significant effects of advertising proved by the ordinary statistical test disappear when the PSWME method is applied. This suggests the possibility that in this case, advertising was concentrated on heavy users of each brand, resulting in a correlation between ad exposures and purchases. The ordinary statistical testing would overlook this bias and mislead marketers to rely excessively on advertising even when it is ineffective; this might be due to over advertising, poor creative work, etc.

This result cannot be generalized to other product categories or markets. In addition, it reveals nothing about the mid- or long-term effect of advertising on purchases, the importance of which has been discussed in several literatures (e.g., Clarke 1976, Dekimpe and Hanssens 1995, Mela, Gupta, and Lehman 1997). Hence, our approach

should be applied not only to the wider range of product categories but also to the deeper aspect of advertising effectiveness in addition to the short-term effect. In doing so, our approach should be extended so as to deal with the repetition effect of advertising, that is, not the occurrence of ad exposure but the frequency of ad exposure. We believe that this can be realized as a natural extension of the theory proposed by Hoshino, Kurata, and Shigemasu (in press).

Despite such limitations, we believe that based on the theoretically rigorous and practically tractable procedure, this study could offer new perspectives on the debate concerning the short-term effect of advertising on sales. By extending this approach to include the mid- or long-term effects of advertising, we will be able to deepen our understanding of advertising effectiveness. However, this is beyond the scope of this paper and will be the aim of our further researches.

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Table 1. Conceptual Framework of Scoring Score Method

		Covariate: x	
		Exposed to a brand's ad: $z=1$	Unexposed to a brand's ad: $z=0$
Buy a brand in ad- exposed incidence: y_1		observed	missing
Buy a brand in ad- unexposed incidence: y_2		missing	observed

Table 2. Results of Ordinary and PSEME-Based Test

Brand	Window	N		Purchase Rate		Ordinary Test on Difference		PS Weighted Purchase Rate		Test by PSWME	
		Ad-Exposed	Not	Ad-Exposed	Not	z-value	p-value	Ad-Exposed	Not	z-value	p-value
1	1	960	223	.163	.161	.039	.485	.172	.205	-.389	.651
	2	880	315	.167	.152	.604	.273	.173	.180	-.141	.556
	3	763	361	.185	.139	1.930 b	.027	.183	.160	.535	.296
	4	827	313	.175	.141	1.408 c	.080	.172	.164	.158	.437
	5	886	329	.158	.155	.128	.449	.157	.188	-.471	.681
	6	915	270	.155	.144	.431	.333	.156	.149	.125	.450
	7	965	280	.147	.118	1.242	.107	.143	.146	-.046	.518
	8	934	303	.128	.112	.745	.228	.127	.136	-.139	.555
2	1	839	344	.558	.517	1.266	.103	.559	.467	.855	.196
	2	711	484	.577	.566	.361	.359	.578	.570	.179	.429
	3	602	522	.568	.510	1.964 b	.025	.550	.542	.173	.431
	4	596	544	.557	.504	1.804 b	.036	.546	.525	.493	.311
	5	691	524	.576	.475	3.487 a	.000	.555	.487	1.214	.112
	6	785	400	.552	.413	4.529 a	.000	.531	.467	.697	.243
	7	857	388	.561	.485	2.515 a	.006	.553	.517	.488	.313
	8	855	382	.574	.521	1.745 b	.041	.577	.532	.599	.274
3	1	137	1,046	.036	.096	-2.287	.989	.032	.096	-1.426	.923
	2	152	1,043	.013	.089	-3.236	.999	.014	.087	-2.008	.978
	3	199	925	.085	.101	-.651	.742	.054	.100	-1.127	.870
	4	252	888	.115	.110	.210	.417	.077	.112	-.973	.835
	5	291	924	.124	.108	.731	.232	.096	.110	-.438	.669
	6	291	894	.141	.110	1.440 c	.075	.121	.112	.178	.429
	7	296	949	.128	.105	1.101	.136	.112	.108	.112	.456
	8	296	941	.108	.088	1.029	.152	.101	.088	.354	.362

a: positive and $p < .01$; b: positive and $p < .05$; c: positive and $p < .10$

Table 3. List of Covariates as Predictors for Logistic Regression

Purchase and Ad-Exposure Experience

- Having purchased the brand in the previous purchase incidence
- Having purchased the brand in the previous quarter
- Exposed to the brand's ad in the previous quarter (Frequency) *

Family Characteristics

- Householder: executive manager
- Householder: self-employed worker
- Householder: office worker/engineer
- Householder: specialist
- Householder: aged 40 or younger
- Householder: aged elder than 60
- A full-time housemaker wife
- At least one pensioner
- At least one pre-school-age child
- At least one elementary/junior-high students
- At least one highschool/college students
- At least one member aged 13 to 25
- At least one member aged elder than 50
- Family size: 3 or less
- Family size: 5 or more
- The number of the female family members *

Housing

- Living in the single house
- The number of bedrooms: 3 or less
- The number of bedrooms: 7 or more

Household Expenditure and Shopping

- Expenditure per month: 200,000 yen or less
- Expenditure per month: 300,000 yen or more
- Shopping everyday
- The member of co-op

Time Period

- In the second quarter in the window
 - In the third quarter in the window
 - In the forth quarter in the window
-

Table 4. Predictive Performance of Logistic Regression

Brand	Window	N	Log. Likelihood	Accuracy ¹⁾	Recall ²⁾	Precision ³⁾	C-statistics ⁴⁾
1	1	1,183	-476.1	.816	.969	.832	.784
	2	1,195	-615.3	.740	.945	.760	.719
	3	1,124	-633.6	.700	.899	.725	.711
	4	1,140	-593.8	.733	.925	.760	.731
	5	1,215	-628.7	.739	.929	.764	.731
	6	1,185	-547.8	.779	.943	.804	.755
	7	1,245	-574.1	.794	.952	.814	.751
	8	1,237	-607.3	.769	.946	.789	.735
2	1	1,183	-600.8	.746	.914	.770	.760
	2	1,195	-756.0	.649	.823	.666	.669
	3	1,124	-725.2	.625	.684	.640	.672
	4	1,140	-739.8	.631	.651	.646	.669
	5	1,215	-731.3	.668	.709	.708	.723
	6	1,185	-618.8	.746	.851	.784	.784
	7	1,245	-665.6	.729	.876	.764	.748
	8	1,237	-672.8	.711	.876	.749	.738
3	1	1,183	-399.5	.884	.000	.000	.672
	2	1,195	-419.1	.872	.000	.000	.717
	3	1,124	-475.3	.819	.060	.429	.719
	4	1,140	-554.3	.780	.079	.513	.695
	5	1,215	-611.7	.766	.096	.571	.703
	6	1,185	-593.1	.753	.100	.483	.724
	7	1,245	-634.8	.764	.061	.529	.683
	8	1,237	-628.7	.771	.098	.644	.686

1) The proportion of correctly predicted incidences among all incidences

2) The proportion of correctly predicted incidences among all incidences observed to be ad-exposed.

3) The proportion of correctly predicted incidences among all incidences predicted to be ad-exposed.

4) The rank-correlation in estimated probabilities for all possible pairs of ad-exposed and not-ad-exposed incidents